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Challenges for remote sensing of the Sustainable Development Goal SDG 15.3.1 productivity indicator

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ABSTRACT

Progress towards combatting land degradation as intended by Sustainable Development Goal 15.3.1 will be monitored using three sub-indicators, of which productivity of vegetation is one. This indicator is to be measured using trends in a remotely-sensed vegetation index. The use of vegetation indices is well-established and remotely-sensed data are readily available. However, their uses for monitoring production that is relevant to sustainable livelihoods have received little attention. This review identifies four areas in the currently-proposed monitoring methodology that are in need of further development. The first is the derivation of primary production from vegetation indices, which requires attention to physiological processes such as light-use efficiency and plant respiration. The second concerns the subsequent steps, in which ecological processes transform the net production into production of goods and services, such as crop products. The third is the need for explicit baselines or reference conditions that specify the productivity in the absence of anthropogenic degradation. The fourth, and most difficult, is to distinguish anthropogenic causes of degradation from potentially similar effects of natural environmental processes. Some of these issues are difficult to tackle with remote sensing alone, although several improvements are available, and others are in development. However, the current use of vegetation indices alone to remotely-sense degradation of ecosystem services does not provide an adequate SDG 15.3.1 productivity indicator.

1. Introduction

The United Nations General Assembly's Sustainable Development Goal (SDG) 15.3.1 concerns degradation of life on land - "to combat desertification, restore degraded land and soil, including land affected by desertification, drought and floods, and strive to achieve a land degradation-neutral world" (Sims et al., 2019). The official indicator of degradation is the "proportion of land that is degraded over total land area". Three sub-indicators form the overall SDG: i. Land cover and land cover change; ii. Land productivity; and iii. Carbon stocks above and below ground (Sims et al., 2019). For large areas, the productivity indicator (ii) is to be measured by negative trends in remote sensing (RS) of multispectral vegetation indices (VIs, e.g. NDVI). Nevertheless, as acknowledged by the "Framework and Guiding Principles for a Land Degradation Indicator" (UNCCD, 2016) "significant challenges remain".

The development in the 1980s of RS techniques capable of measurement of vegetation at a frequency adequate to track its sub-seasonal and annual changes, revolutionized major aspects of the biospheric sciences. Spectral VIs are now used in a wide variety of routine and research applications including monitoring primary production. There has been enormous improvement in many aspects of the VIs, among which are radiometric precision, atmospheric corrections, geospatial location, spatial resolution, and frequency of acquisition (Yengoh et al., 2016). However, the complexity of the physiological and ecological processes that determine how changes in VIs are related to degradation of ecosystem services (Millenium Ecosystem Assessment, 2005) is not one of them.

SDG 15.3.1 requires measurement of anthropogenic land degradation, but natural environmental processes can result in the exact same symptoms. For example, erosion can be initiated by human activities or natural geomorphological processes and salinization can be a result of a natural movement of water towards the surface or by excessive irrigation, or both. However, natural and human-induced stresses obviously have different origins. Detection of the anthropogenic component and understanding the nature of the interactions with natural processes is not easy. It is further complicated by the fact that the relationships of stress and productivity may be non-linear (Walker et al., 2002). The type of response of the vegetation has important implications, particularly for restoration. For instance, land degraded by anthropogenic stress may be resilient, recovering once the stress is relieved, or it may enter a permanent state of degradation from which recovery is impossible, no matter the amount of reduction in stress. Rarely, if ever, is

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this distinction discussed, yet it is well known in vegetation science and has enormous significance for the management of degradation.

Measurement of degradation requires more than detection of temporal trends of VIs. The “Good Practice Guidance document” (Sims et al., 2017) provides a number of methods for measurement of productivity for SDG 15.3.1. Nonetheless, it makes no reference to the steps needed to link productivity to human livelihoods. The complete relationship between remotely-sensed VIs and ecological services that are the determinants of sustainable development (Sims et al., 2019), involves multiple steps which are currently omitted. Maps showing trends of VIs are compelling but are not direct measurements of the type of degradation that is relevant to sustainability. Without attention to how VIs are used to infer degradation of ecosystem services, their use is misleading and may be completely meaningless.

2. Normalization

Since both anthropogenic and natural processes can cause degradation, it is critical that these two are distinguished for monitoring of SDG 15.3.1 (Orr, 2011). A number of methods have been used to eliminate natural degradation and thereby reveal any anthropogenic component. For example, because productivity is strongly related to precipitation in drylands, a common normalization transforms NDVI to NDVI per unit precipitation, known as the rain use efficiency (RUE; Prince et al., 1998). Le Houérou (1984) used RUE to indicate the biogeographic relationships of average productivity with climatological precipitation at a regional scale, as have others (e.g. Huxman et al., 2004; Ruppert et al., 2012). However, there is an important distinction between Le Houérou's application of RUE to biogeography, and its use for normalization of productivity to detect degradation since it is at the scales of individual pixels and short periods of time (Prince et al., 1998). These two applications are often confused.

More recently the residual trend (RESTREND) technique has become popular (Wessels et al., 2007). It consists of calculation of the RUE of non-degraded pixels, followed by plotting the residuals of subtraction of the VIs of degraded from the estimated non-degraded pixels against time. Negative trends in residuals are interpreted as degradation and positive trends as recovery. Variations in other limiting factors can be normalized similarly (Cho et al., 2015; Rishmawi and Prince, 2016; Wylie et al., 2008). RUE highlights the precipitation-productivity relationship while RESTREND emphasizes temporal trends; however, they are both transforms of the same variables. Trends in short time-series of residuals can be summarized with a linear regression, but longer sequences of data often show changes in trends, and so piecewise regression is now widely used (Verbesselt et al., 2010; Liu et al., 2019). A valuable feature of RUE/RESTREND is that they track single pixels (or whatever spatial units are used). Consequently, they automatically allow for any static environmental differences (e.g. soil, topography, fertility) that are not relevant to anthropogenic degradation.

RUE/RESTREND generally assume that precipitation is entirely available to vegetation, but the amount of water that reaches the root zone can be significantly different from the annual total precipitation (Prince et al., 1998; Rodriguez-Iturbe, 2000; Kutsch et al., 2008). “Effective” precipitation is determined by many aspects beyond annual or growing season totals. These include (Prince et al., 1998): i. Seasonal timing, since there are differences in the growth response at different stages in the growing season (Ivits et al., 2012; Rishmawi et al., 2016); ii. Losses due to direct soil evaporation and from canopy interception; iii. High rain rate which results in run-off; iv. The amount of infiltration (Kumar et al., 2002); v. Run-off and run-on from adjacent land; vi. Drainage from the rooting zone; vii. Low soil hydraulic conductivity which reduces flow from the surface to the root zone; and viii. Existing water stored in the soil or vegetation. Some of these components of the water cycle may be susceptible to degradation, and so it is not surprising that RUE/RESTREND values are frequently still related to precipitation even after annual precipitation normalization (Fensholt and Rasmussen, 2011). Furthermore, because these components often vary between sites, geographical differences in RUE/RESTREND do not necessarily indicate degradation.

Not infrequently, precipitation in preceding years (“antecedent”) is correlated with production in the following years, a phenomenon sometimes referred to as “memory” or “lags” (Goward and Prince, 1995; Ruppert et al., 2012). There are several possible causes of lags: i. Formation of more or fewer seeds or perennating buds that result in changes in production in subsequent years. ii. Changes in allocation of assimilated carbon to storage organs that may alter production in following years. iii. Changes in species composition, leading to differences in competitive relationships in subsequent years. iv. Changes in soil and crustal microbial communities, leading to changes in nutrient mineralization. v. Changes in litter accumulation that can change infiltration in the following years. A particularly important source of delayed responses is fire, which can both increase (e.g. by release of nutrients from biomass) and reduce productivity during regrowth (e.g. slow post-fire seedling establishment, slow regrowth of fire-resistant species).

A wide variety of factors in addition to precipitation can affect productivity, and some more comprehensive environmental normalizations could usefully be considered for SDG 15.3.1. For example, in the Sahel, Rishmawi et al. (2016) used a soil-vegetation-atmosphere-transfer model calibrated at flux sites and found that temperature, specific humidity, and the seasonal distribution and total precipitation were significantly related to productivity. In the Negev, Gutterman (2000) found day length, rate of seed maturation, and dispersal of seeds were important factors as well as the amount and seasonality of precipitation.

A more fundamental problem with RUE/RESTREND is that productivity, or growth, is slow and therefore responds relatively slowly - from weeks to years - to environmental changes, be they anthropogenic or natural. Precipitation, on the other hand, typically varies from minutes to years. Thus, productivity has a “slow” response while precipitation is a “fast” variable (Carpenter and Turner, 2000). The mismatch of temporal scales can cause dramatic temporal fluctuations in RUE/RESTREND without any change in productivity. For example, even with no difference in productivity, RUE (production/precipitation) will be high in dry years (low denominator) and low (high denominator) in wet years. Valid use of RUE/RESTREND for normalization, therefore, requires scaling temporal variation of precipitation to the temporal response of productivity. A simple approach is averaging the precipitation and production over a number of years (Prince et al., 1998), however, the appropriate number can be uncertain.

3. Reference baselines

Degradation is a relative condition - a change compared to a non-degraded condition. Thus, degradation can only be measured by comparison with a reference (Cowie et al., 2018; Prince et al., 2018). An obvious approach would be a comparison with known, non-degraded sites (Verón and Paruelo, 2010; Wessels et al., 2004), but the locations of such sites are, unfortunately, rarely known. Furthermore, they may not exist in the study area, the entire area may have been degraded in the past, or there may be no degradation present.

In the absence of known, non-degraded field sites, RUE/RESTREND substitutes the production per unit precipitation, estimated by the coefficient of a linear regression of the production of non-degraded sites on precipitation. Other environmental variables can be added if they also affect productivity. Unfortunately, since which pixels (if any) are not degraded is unknown, all pixels, including degraded, must be included and the regression coefficient therefore underestimates the reference condition. Upper quantile regression has been used to reduce the effect of the mixture (Rishmawi and Prince, 2016; Ruppert et al., 2012). However, the non-degraded, potential production is inevitably, still underestimated.

RESTREND also needs a reference for interpretation of trends.

Generally, the significance of the slope coefficient is used (Wessels et al., 2012). If a longer time-series is available, it can be segmented and individual regressions fitted to shorter periods in order to resolve changes in degradation and recovery within the time-series (Burrell et al., 2017). However, these are arbitrary baselines, since the condition with least degradation is unknown, or degradation may have occurred before the time-series begins. An inverse method is sometimes used, by identification of sites that are fully degraded. For example, the "grazing gradient" technique which uses the conditions around livestock water sources as a fully-degraded reference and compares it with the rest of the study area (Pickup and Chewings, 1994).

Local NPP Scaling (LNS) is a quite different approach which attempts to identify reference sites without the need for external knowledge of non-degraded or fully degraded sites (Ivits and Cherlet, 2013; Jackson and Prince, 2016(a); Noojipady et al., 2015; Prince et al., 2009). It starts with classification of the entire study area into homogeneous land capability classes (LCCs) using all available environmental factors that affect productivity, other than anthropogenic factors. It is assumed that all pixels in a single LCC would have the same productivity in the absence of degradation. Without the LCCs, there would be a danger of mixing intrinsically more and less productive land. For example, a large Navaho reservation in SW USA appeared to be degraded, but the use of LCCs identified it as an area of intrinsically lower productivity (Noojipady et al., 2015), questioning the common opinion that the entire reservation had been poorly managed. The designation of LCCs is followed by an analysis of a frequency distribution of the productivity of all pixels in an LCC to identify the pixels with the maximum productivity. To suppress outliers, the productivity at an arbitrary limit is used rather than the absolute maximum. This maximum production is used as a best estimator of areas that are not degraded. The degree of degradation in each LCC is determined by subtraction of the production of every pixel from the non-degraded, reference NPP. Since LNS is in production units, it is directly relevant to degradation. The principal drawbacks of LNS are the assumptions that the LCCs are sufficiently internally homogeneous and that the maximum productivity in each LCC is a good estimate of the potential.

4. Degradation and vegetation dynamics

4.1. Vegetation processes

Degradation of vegetation is not simply determined by the environment, be it natural or anthropogenic, rather there are vegetation processes that can modify or even reverse the effects of reduction in productivity (Scoones, 1992). Changes in VIs are often interpreted as evidence for degradation without consideration of these processes (Fig. 1). This is a gross oversimplification. In reality, there is a sequence or chain of stages between remote sensing and the ecosystem service (Sims et al., 2019). Hierarchy theory (Bergkamp, 1995; Prince, 2002) addresses the sequence in complexity and clarifies point in the chain responsible for any subsequent modifications in productivity and hence on human livelihoods.

The place of RS in measurement of degradation is at the start of the chain (Fig. 1, stage 1) in which reflectances are used in generally, simple radiative transfer modeling (stage 2) to derive information about vegetation, typically VIs. This is followed by physiological (stage 3) and ecological (stage 4) processes, from which the functional variables that affect ecosystem services emerge (stage 5). In the physiological stage, absorbed photosynthetically-active radiation (APAR) drives photosynthesis which leads to primary production. However, the relationship between APAR and biomass production is subject to additional processes that are far from constant (Porporato and Rodriguez-Iturbe, 2002; Schulze et al., 2005), including respiration, allocation of production to above and below ground parts, phenological constraints and other differences in plant functional types. In simple light use efficiency models of NPP, these factors are summarized in an efficiency parameter (Prince, 1991; Ruimy et al., 1994) but its measurement is difficult.

In the ecological stage, community processes transform the NPP into products available for human use. However, an increase in NPP might be confined to non-economic components of the vegetation, in which case a decline in the VIs does not indicate degradation of ecosystem services. The ecological stage includes plant competition, decomposition and mineralization in the soil, herbivory and disease. The processes involved in the ecological services, the final step (stage 5), are not considered here since they are in the realm of socio-economics and human choices (van der Esch et al., 2017). This is not to say these are unimportant (Turner et al., 2007; Walker et al., 2002), rather they belong to the overall interpretation of the SDGs, not 15.3.1 alone.

Each link in the chain uses outputs from the previous one, often with additional inputs, ultimately leading to ecological services (stage 5, crop products). The input from the previous stage may be linearly related to its output, in which case omitting it only affects the units. For example, VIs are often used as a surrogate for primary production, which can hold true in some conditions (Fensholt et al., 2006), although it is actually related to the gross primary production (GPP). In most RS of degradation, the results are given as VIs or production calculated by regression on NPP obtained from other sources (e.g. MODIS MOD13Q1; Bai et al., 2008(a)). However, the output of any stage may be damped in the next one and have little further effect, or may even be amplified (Ash et al., 2002; Herrmann and Tappan, 2013). The current method for derivation of the SDG 15.3.1 productivity indicator depends on VIs alone which are therefore assumed to be directly related to livelihoods, skipping the physiological (3) and ecological (4) stages in the chain. The omission of these stages means that changes in VIs may or may not indicate ultimate degradation of livelihoods in stage 5. The Famine Early Warning System (FEWS, Funk et al., 2019) is an example of how

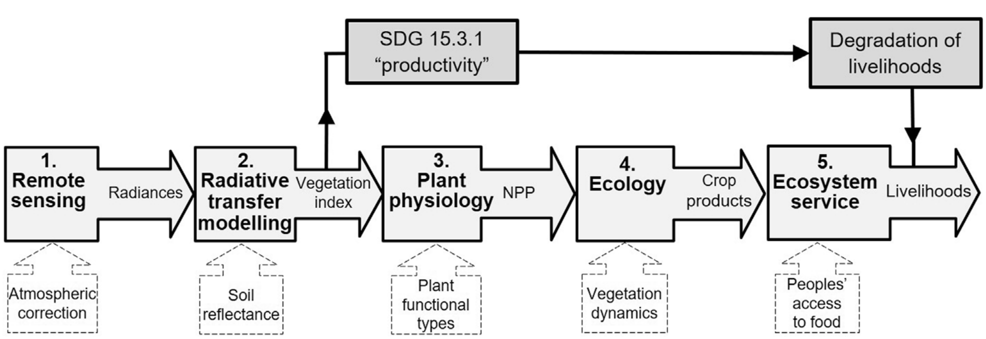

Fig. 1. The logical sequence of stages between (1) remotely-sensed measurements and (5) degradation of ecosystem services - illustrated using provision of food. The stages are: (1) Spectral radiances measured by remote sensing; (2) Radiative transfer modelling to derive surface reflectances and vegetation indices; (3) A physiological stage in which vegetation indices provide an estimate of absorbed photosynthetically-active radiation (APAR), used to model net primary production (NPP); (4) An ecological stage in which NPP is transformed into crop yield; And (5), the effect of degradation of productivity on human livelihoods - in this example harvested crop products. In each stage there are additional factors (examples are shown in the lower, dashed boxes), some of which can also be subject to degradation. The current indicator for SDG 15.3.1 (productivity sub-indicator) uses only the outcome of stage 2 to measure degradation (upper boxes), skipping further processes that affect human livelihoods. (Note; there are more complex representations of these processes that include, for example, feedbacks and interactions, but the simple representation here is adequate to illustrate the point.)

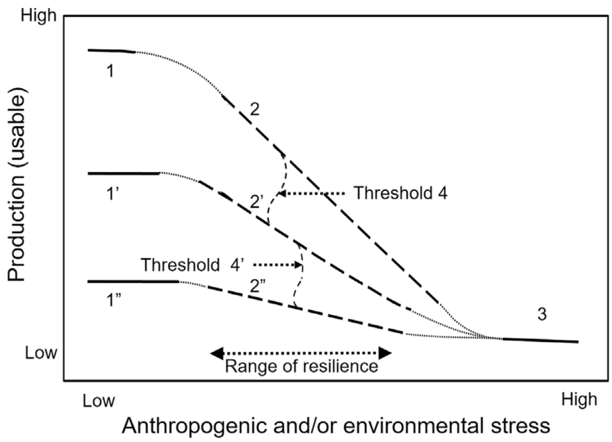

Fig. 2. Response of productivity to stress caused by humans and/or the natural environment. At low stress there is no effect on productivity, as indicated by the horizontal line in stage 1. As stress increases, productivity declines (stage 2), ultimately to very low values (stage 3). In stage 2, productivity is resilient, increasing or decreasing depending on the prevailing intensity of stress. Under certain conditions, however, productivity can diverge, passing over a threshold (stage 4), to a new resilient trajectory (2′). Once over a threshold, productivity cannot naturally return to the previous level, no matter how much the stress is alleviated. One or more thresholds may occur (stages 4 and 4′), each followed by new resilient stages (2′ and 2″). The succession model is illustrated by stage 2, 2′ and 2″, the threshold model by the trajectory from stage 2 to 2′ and 2′ to 2″, and the state and transition model by all stages. Note, the production shown in the figure is just that component of total primary production that is useable by humans.

VIs and other factors contribute to a final assessment of productivity relevant to an ecosystem services goal.

4.2. Stress responses

There is a multiplicity of factors that can stress vegetation and degrade productivity (Schulze et al., 2005). However, the term ("stress") is misleading since what are normally regarded as forms of anthropogenic degradation can actually increase productivity. For example, conversion from grassland to intensive cultivation, the excessive use of artificial fertilizers, nitrogen deposition from a polluted atmosphere, anthropogenic increases in carbon dioxide and anthropogenic climate changes that can all lead to increases in produvtivity.

Differences in the intensity of anthropogenic and/or environmental stress lead to complexity in vegetation dynamics (Fig. 2). In years and sites with very low stress and productivity is at a maximum (Fig. 2, stage 1). As stress increases (anthropogenic or environmental or both (Prince et al., 2018)), there is an approximately linear phase (stage 2) in which productivity is directly related to the stress. Finally, at high stress, productivity drops to a very low value (stage 3) and changes very little, even if the stress continues to increase. This relationship can be illustrated by a "response curve" (Fig. 2) (Schulze et al., 2005). Since stress induces little change in productivity in both low (1) and high (3) stress, they can be impossible to distinguish by productivity measurements alone, without a baseline.

In most RS studies the effect of a stressor is assumed to be linear throughout, omitting stages 1 and 3. Bai et al. (2008(b)) and others eliminated pixels where NDVI had no significant correlation with precipitation which, while avoiding confusion between the initial and final invariants stages, confined the analysis to pixels in the linear, resilient phase. However, productivity under stress may not follow a simple logistic response curve (Lockwood and Lockwood, 1993). There are three concepts that can relate the different aspects of the stress responses to each other. First, succession (Schulze et al., 2005), in which productivity actually does follow a simple response curve. It has dominated thinking about vegetation for the last 100 years and it is widely used to manage rangeland. While the traditional concept of succession is uni-directional, from a pioneer to a semi-stable climax sate, in its application to degradation it can be reversed by stress, so productivity can increase and decrease repetitively as the intensity of stress changes (represented by the lines in Fig. 2) (Wessels et al., 2004). The response of productivity to fluctuations in stress is called "resilience" (Walker et al., 2002). A second parameter, "resistance" is sometimes used to describe the rate at which productivity changes as a result of a change in stress.

The second concept of vegetation dynamics, sometimes known as the threshold model, envisages a situation in which vegetation, initially in stage 1, is subject to an increase in stress and proceeds to the resilient stage 2. Then, at some point (stage 4), productivity drops suddenly, and the vegetation enters a degraded condition (stage 2') (Eve et al., 1999). Most important, it cannot recover to stage 2, no matter how much the anthropogenic and environmental stressors decline (Ratajczak et al., 2014; Rietkerk et al., 2004; Walker et al., 2002). At the threshold (sometimes called a tipping or bifurcation point) there are changes in resilience and resistance (Hu et al., 2018). There are also fundamental changes in processes (Kinzig et al., 2006), including positive feedbacks (Rietkerk et al., 2004) and other mechanisms that maintain or reinforce the new state. For example, in drylands, transitions among various grassland types and their productivity can be reversible with grazing management (resilient), but excessive grazing or an extreme event such as fire can lead to invasion and dominance by woody species (Fuhlendorf and Smeins, 1997). No amount of reduction of livestock numbers will reverse the transition and the vegetation has entered a stable degraded state. This transition is very important since production is lost and can only be restored by drastic management procedures (Walker et al., 2002) that are usually prohibitively expensive. For example, restoration after the 1930s US "Dust Bowl" in the southern plains of the US (Hurt, 1986) cost approximately $17 billion (in 2017 US$ value) (Baveye et al., 2011).

In addition to the succession and threshold concepts, there is a third, the "state and transitions" model (Helman et al., 2014; Stringham et al., 2003), which includes multiple transitions separated by thresholds. This concept actually encompasses the successional and threshold models (Briske et al., 2005) (Fig. 2). Evidence for the existence of multiple stable states detected in RS data has been provided by Wessels et al. (2004), while assessing the effects of human-induced land degradation in the former homelands of South Africa. It was found that the degraded state persisted in spite of subsequent increases and decreases in precipitation. In a wet year, the productivity of a degraded site was sometimes higher than a non-degraded one in a drier year, providing evidence of resilience within a degraded state, as indicated by curves 2' and 2″ in Fig. 2. Interestingly, the differences in productivity between degraded and non-degraded sites, even in years with extreme low and high precipitation, was almost constant at only 9%, suggesting that further transitions might be possible, as included in the state and transitions concept.

All three of the models described above refer strictly to the dynamics of useable production (see the ordinate in Fig. 2). Examples where parts of the total production are not useable include bush encroachment (Ratajczak et al., 2014) and invasion by *Pteridium aquilinum* in UK (Marrs et al., 2000), but in which the invader increases total NPP (Birhane et al., 2017). In this case, if total NPP is used as a metric of degradation, it may seem that degradation is reversed. Another critical point is the effect of drastic changes in land use, such as clearance of natural vegetation, which might initially be thought of as degradation. However, following the transition, the low stress condition is the one in which useable production (e.g., crop yield, lumber offtake) occurs, and the causes of increase in stress includes the new management factors such as over application of fertilizers and pesticides, less control of weeds, and over irrigation. Once under human management, the anthropogenic and environmental factors that determine productivity are radically changed, and the response curve models should be reset.

5. Discussion

The current productivity indicator for SDG 15.3.1 consists of trends in VIs, but application to detection of degradation needs to go beyond this. The "Good Practice Guidance" (Sims et al., 2019) recommends RUE/RESTREND for measurement of degradation. While these are legitimate metrics their interpretation is not straightforward (Ruppert et al., 2012).

One issue is the need to control ("normalize") factors that affect productivity but are not related to degradation, including anthropogenic degradation. RUE/RESTREND uses single or multiple individual variables as divisors, but this assumes oversimplified relationships with productivity (Ardö, 2011). This is a significant problem, and it is difficult to imagine a complete solution using current methods. For the future, a promising approach is the use of simulation models that use representations of the actual physiological and ecological processes, rather than statistical models such as regressions (Ardö, 2011; Boer and Puigdefábregas, 2005; Conijn et al., 2013; Tracol et al., 2006). If run without anthropogenic effects, process-based models could provide a more appropriate measure of non-degraded reference productivity. All models, however, are limited by the availability, accuracy and spatial resolution of the inputs. Currently the resolutions are often very coarse (Ali et al., 2005), albeit with high temporal resolution. Thus, applications at present are limited to large-area processes such as overgrazing in extensive pastoralism, degradation by atmospheric pollution or regional climate change. However, improvements in RS data are in progress giving new types of data, greater accuracy and the finer resolution which is relevant to human activities.

Beyond RS of VIs there are aspects of degradation that involve intrinsic processes of the vegetation, in both physiological (Izaurralde et al., 2005) and ecological (Hu et al., 2018) stages. Although not included in the indictors for SDG 15.3.1, these are the proximate causes of degradation of ecosystem services (van der Esch et al., 2017) and apply no matter what the spatial and temporal scales. In by far the majority of reports of degradation the vegetation is actually in a resilient phase which, by definition, is capable of reversal and recovery when the causative stressors are reduced or cease. For example, RESTREND often has both negative and positive periods that extend over several years (Bai et al., 2008(b)). According to some definitions, this does not constitute "degradation", even though it may appear so for a period of time (Sheikh and Soomro, 2006). There is confusion on this point and, in many cases, the meaning is not specified (Secretariat of the United Nations, 1999). A salutary example of this confusion is the supposed degradation ("desertification") of the Sahel during the 1980s drought (Herrmann and Sop, 2016). This apparently permanent degradation, which became an icon of desertification, was reversed when the drought ended and the vegetation recovered. On the other hand, the "Dust Bowl" of the southern plains of the United States (Hurt, 1986) did not reverse naturally, even when the drought and inappropriate cultivation ceased. In this case, the degradation was permanent. Because of the enormous significance of these differences in relation to management and human livelihoods, there is good reason to distinguish the two, perhaps with terms such as "permanent degradation" and "temporary degradation". The "Good Practice Guidance" (Sims et al., 2017) does not recognize this distinction.

There are a wide-range of data that would augment detection of degradation by VIs alone. More detailed mapping of land cover using high spatial resolution, multispectral data at 4 m or finer resolution is very promising (Zhihuan et al., 2018) since it enables detection of degradation at the scale of human activities. At present, the use of this high-resolution RS data is limited to qualitative, visual interpretation. However, there is scope for the application of automated pattern-recognition (Cheng and Han, 2016; Holloway and Mengersen, 2018; Zhihuan et al., 2018) to discriminate more conditions and provide more objective data. This would also improve the land cover sub-indicator of SDG 15.3.1. Land cover classification could also be improved with imaging spectrometry (Asner and Heidebrecht, 2003).

Other aspects of degradation of vegetation are also available. These include measurement of dry season, standing dead vegetation using the cellulose absorption index (CAI) (Daughtry, 2001; Jackson and Prince 2016(b)), important because the amount of standing dry biomass is the proximate control of livestock production in the dry season. The spatial patterns of vegetation and biomass can be measured using LiDAR (Fisher et al., 2015) and some types of RADAR (de Jong et al., 2011; Metternicht et al., 2010). Some progress is also being made in detection of species composition (e.g. Hunt et al., 2003). Better known methods include detection of bare ground using albedo (Zhao et al., 2018), increases in diurnal temperature ranges (Zhou et al., 2007), fire (Potter et al., 2003), and dust emissions (Ginoux et al., 2012).

6. Conclusions

Consistent, long-term data on trends and other aspects of vegetation are of great value for monitoring degradation of productivity. RS provides the only techniques to do this from local to global scales. However, the methods currently recommended are only a first step to detection of degradation of ecosystem services, which is the focus of the Sustainable Development Goals. Currently, determination of the relationship of VIs to productivity, detection and exclusion of non-anthropogenic processes and establishment of valid baselines, are all absent from the recommendations for measurement. Beyond these is the matter of the vegetation processes that connect NPP to the broader context of SDG 15.3 and its interactions with other SDGs. A cogent example of an application of RS of VIs that goes beyond the use of VIs alone, is the Famine Early Warning System (FEWS, Funk et al., 2019). The current oversimplifications (Sims et al., 2019) lead to misunderstanding of the significance of the productivity indicator. Of course, in some cases, VIs may be all the information that is available, but the relevance to human livelihoods is likely to be limited and should always be stated explicitly.

RS has and will continue to make a fundamental contribution to the assessment of degradation but monitoring of productivity for SDG 15.3.1 cannot be achieved using spatial and temporal comparisons of VIs alone. Progress will depend on matching the continuing effort put into the development of new "retrievals" of surface properties by RS science with attention to the physiological and ecological processes that make net production relevant to ecosystem services. Progress beyond VIs is possible and has been applied in some cases (Herrmann et al., 2014; Seaquist et al., 2009; Symeonakis and Drake, 2004). However, a fundamental difficulty is the separation in disciplines between RS and ecological sciences. Since current techniques do not provide the information expected from SDG 15.3.1, there is an urgent need for coordinated and comprehensive research and development (Yengoh et al., 2016). Enhanced communication between research in RS technology and users of RS for measurement of degradation is needed. This interaction will most likely occur in a formalized research and development program that is not entirely subject to the vagaries of institutional research funding.

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